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Modeling Cumulus Cloud Scenes from High-resolution Satellite Images

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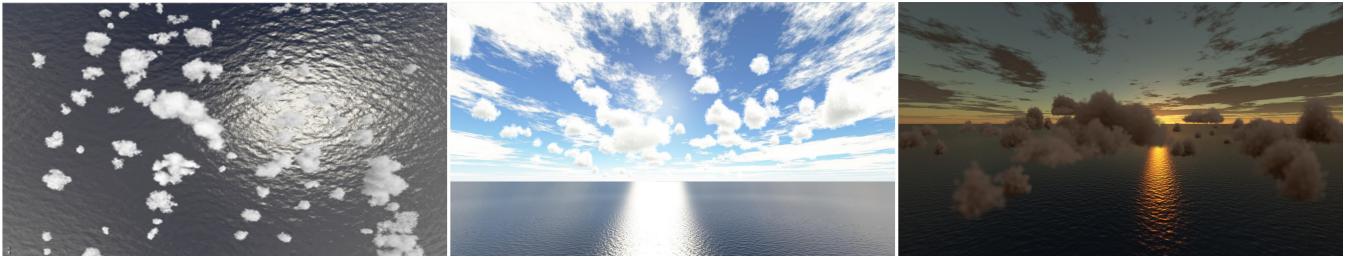


Figure 1: Our physically based method can automatically reconstruct large-scale cumulus cloud scenes from high-resolution satellite images. A key aspect of our approach is that we extract necessary features for modeling clouds to ensure that the simulation results can be physically sound.

Abstract

We present a reconstruction framework fitting physically-based constraints to model large-scale cloud scenes from satellite images. Applications include weather phenomena visualization, flight simulation, and weather spotter training. In our method, the cloud shape is assumed to be composed of a cloud top surface and a nearly flat cloud base surface. Based on this, an effective method of multispectral data processing is developed to obtain relevant information for calculating the cloud base height and the cloud top height, including ground temperature, cloud top temperature and cloud shadow. A lapse rate model is proposed to formulate cloud shape as an implicit function of temperature lapse rate and cloud base temperature. After obtaining initial cloud shapes, we enrich the shapes by a fractal method and represent reconstructed clouds by a particle system. Experiment results demonstrate the capability of our method in generating physically sound large-scale cloud scenes from high-resolution satellite images.

CCS Concepts

•Computing methodologies → Modeling methodologies; Volumetric models;

1. Introduction

Modeling complex real world objects and scenes, such as fluid, smokes, and clouds, has been attempted in both graphics and vision [Thu16, YLH*14]. Cumulus clouds play an important role in enhancing the visualization quality of simulated outdoor scenes, earth view from outer space, and weather phenomena. Cloud’s complex shape, topological diversity, and non-Lambertian appearance make it challenging for constructing a 3D cloud model. Es-

pecially constructing large cloud scenes with hundreds of clouds is undoubtedly very tedious.

In this work, our aim is to automatically reconstruct large-scale cumulus cloud scenes from satellite images by using physically based methods. Many methods have already been proposed for modeling cumulus clouds, which are done by a procedural approach or an approximated meteorological model. These methods rely on some optical and shape parameters obtained by subjective judgement. So they can hardly produce a physically sound cloud shape. On the other hand, a satellite image usually contains hundreds of clouds, where each has a specific shape and position, com-

prising a large number of parameters. Hence, modeling large-scale cloud scenes will undoubtedly be tedious and difficult. In contrast, our method automatically extracts relevant information from satellite images to model physically sound cloud scenes.

As the sensors of a polar-orbit satellite are directed toward the Earth's surface, another key challenge for our work is to get the information about the vertical dimension of clouds from satellite images. In terms of spatial resolution, satellite images can be classified into two types: low-resolution images (several kilometers) and high-resolution images (hundreds to tens of meters). For low-resolution images, several methods have been proposed to model earth-scale clouds. At such a scale, a cloud is represented as a thin plate without an accurate thickness, a realistic rendering can only be achieved by generating an approximate layer-like volumetric representation [DYN09, YLHY13]. These methods are therefore not suitable for modeling cumulus clouds whose vertical sizes are salient comparing to horizontal sizes. Furthermore, the structure of cumulus clouds cannot be well recorded or even observed in low resolution images because the typical size of cumulus clouds is usually approximately several hundreds of meters and thus smaller than the pixel size. However, high-resolution satellite images, such as Landsat7/8, Terra and Aqua, have more accurate information than low-resolution ones to support the modeling of cumulus clouds. In these images, the shadow of a cloud is distinct and indicates the altitude of the cloud base. With cloud shadows and a temperature lapse rate model that establishes the relationship between temperature and altitude, our method can calculate the implicit height information for reconstructing 3D cloud scenes.

In summary, our main contributions are as follows:

- A physically based automated framework is established to model large-scale cumulus cloud scenes from satellite images.
- An automatic method is developed to identify and extract suitable features from satellite images for reconstructing 3D cumulus clouds. This is challenging since satellite images comprise a wide range of features representing different types of objects, and particularly not all necessary features for cloud reconstruction are directly available.
- A lapse rate model is developed to relate temperature and cloud altitude, providing essential inputs to derive 3D cloud shapes by maximizing the similarity between observed and calculated cloud shadows. This is challenging since each cloud has a distinct temperature lapse rate in a large-scale scene, while the cloud base temperature is not available.
- A propagation procedure is established to search the optimal parameters for each cloud progressively from a set of feasible solutions, in order to efficiently model a large-scale cloud scene.

2. Related Work

Modeling and rendering are two main topics about cloud animation in computer graphics. Much work concerns itself with rendering participating media [YIC*10, Har05, Yus14, SDS*16]. Meanwhile, a large number of methods have also been proposed to model cloud shapes [Har05, DSY10, YLH*14, JC16]. We will limit ourselves to the topic of modeling in this paper.

Mainstream methods utilize either a procedural approach or a

physically based method. The former mainly relies on the selection of parameters, which includes methods based on fractals [Vos83], textured ellipsoids [Gar85], noise function [Ebe97], spectral syntheses [Sak93], and interactive design [WBC08], while the latter is based on a simplified atmospheric model for simulating the formation processes of clouds [Har05, DKNY08]. Although both approaches can generate visually impressive cloud scenes, they have difficulty in generating physically sound cloud shapes and large cloud scenes due to the complex relation between the results and the input parameters.

With the availability of cloud-related data, the data-driven methodology enables an intuitive and physically meaningful solution for modeling clouds. There are three types of cloud-related data: satellite images [DNYO98, CAJB*08, DYN09, YLHY13], simulation data [REHL03, HHS07], and photographic images [DSY10, YLH*14, JC16]. In contrast to simulation data and photographic images, satellite images, recording multi-spectral radiation information, contain more available information for modeling physically realistic clouds and large-scale cloud systems. There have been much work about cloud detection, extraction and modeling from satellite images [Cha12, GP15]. Based on the infrared image, two different methods [LKS96, DYN09] are used to construct a cloud top surface. They assume the cloud top height is proportional to the intensity of the infrared image. The difference between the two methods is that [LKS96] uses only the cloud top surface to model clouds, while [DYN09] represents clouds using a density volume near the cloud top surface. Unlike these methods, [DNYO98] does not intend to directly derive the geometry of a cloud, but inverts the density distribution of the cloud from a simple lighting model. Overall, these methods only focus on producing realistic-looking earth-scale clouds but pay little attention to the physically sound 3D structure of cumulus clouds.

Closely related to our method, [YLHY13] and [YG15] have proposed some physically based methods to infer the shape of clouds from satellite images. However, they assign a uniform lapse rate for all clouds, which is not correct for large-scale cloud scenes. To handle the problem, we proposed a lapse rate model to calculate a unique lapse rate for each cloud by maximizing the similarity between observed and calculated cloud shadows.

3. Data Processing

The input data to our system are five-band satellite images, including blue (BLUE, 0.450-0.515 μ m), red (RED, 0.630-0.680 μ m), near infrared (NIR, 0.845-0.885 μ m), shortwave infrared (SWIR, 1.560-1.660 μ m), and longwave infrared (IR, 10.620-11.190 μ m). For each pixel, the first four bands record the reflectance \mathcal{R}_i for $i = \text{blue}, \text{red}, \text{nir}, \text{swir}$, indicating the ratio of the reflected intensity to the incident solar flux density, and the last one records the temperature T_{ir} . In particular, the NIR image is linearly mapped to a grey image, as shown in Fig.2(a).

Fig.3 shows the main steps of our method. In the following, we present an algorithm for pixel classification and an approach to obtain the ground temperature and the cloud top temperature. We also formulate a method to compute cloud shadows.

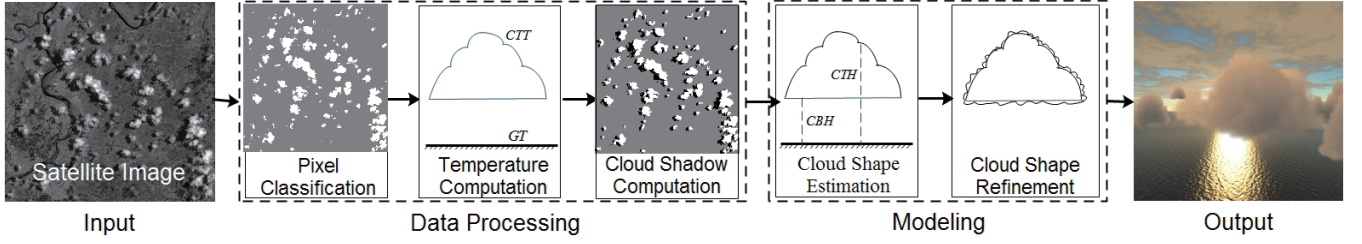


Figure 3: Overview of our framework

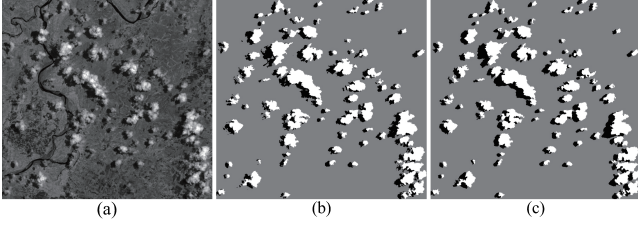


Figure 2: (a) The NIR image is linearly mapped to a gray-level image. (b) Image pixels are divided into three types: cloud (white), original shadow (black) and background (grey). (c) The calculated shadow (black) is formed by projecting the calculated shapes of clouds onto the ground.

3.1. Pixel Classification

Pixel classification is the basis to identify relevant cloud information. Cloud pixel detection has been performed by the Automated Cloud Cover Assessment (ACCA) system [IBGA06]. Due to its complexity, we do not adopt it but use a comparable algorithm [OWV11]. The algorithm uses four sets of decision rules to flag a pixel as cloud, non-vegetated land, vegetated land, snow/ice, or water based on bands BLUE, RED, NIR and SWIR. With a minor modification, the thermal IR image is used to eliminate pixels with temperatures of more than 300K because clouds are colder than this threshold. So, the pixels are divided into cloudy and cloud free. We further use the information of four-neighborhood of a pixel to remove noise. Finally, cloudy pixels are clustered into connected regions, and each region is treated as a cloud (Fig. 2(b)).

3.2. Temperature Computation

The task of this section is to estimate the ground temperature T_g and the cloud top temperature T_{ct} . In a local region, the ground temperature remains roughly the same. We can then approximate the ground temperature of each cloud using the mean temperature of cloud-free pixels within an isometric zone $\{p : |p - C| < R, p \text{ is a background pixel}\}$, where C and R are the center and radius of the cloud, respectively.

The cloud top temperature can be derived by the following process. For a cumulus cloud, the pixels in the central region have a large optical thickness, and the ground infrared radiation is hardly sensed by the satellite. The recorded temperature T_{ir} in the IR

image can be approximately treated as the cloud top temperature T_{ct} . However, in the boundary region, cloud has a small thickness, and the measured temperature is usually higher than the actual temperature due to the contribution of the infrared radiation from the ground. As a result, the infrared radiance received by the satellite is a linear combination of the ground radiance and the cloud radiance as follows:

$$B_\lambda(T_{ir}) = (1 - \epsilon)B_\lambda(T_g) + \epsilon B_\lambda(T_{ct}) \quad (1)$$

where λ denotes the central wavelength at band IR, ϵ is the cloud emissivity, and $B_\lambda(\cdot)$ is the Planck function. In particular, the cloud emissivity ϵ relates to the optical thickness τ based on the following equation:

$$\epsilon = 1 - \exp(-\tau) \quad (2)$$

From Eqs. (1) and (2), the cloud top temperature T_{ct} is determined by the optical thickness τ . To compute τ , we use the reflection function in the Red band [KR04, YLHY13]:

$$\mathcal{R}_{red} = \mathcal{R}(\tau, \zeta, \omega, \theta_s, \theta_v, \phi_s, \phi_v) \quad (3)$$

where \mathcal{R} is the reflection function, ζ is the asymmetry factor, and ω is the single scattering albedo. The zenith angle θ_v and azimuth angle ϕ_v of the satellite can be derived from the orbit-geometry, and the zenith angle θ_s and azimuth angle ϕ_s of the sun are recorded in the metadata file of the Landsat-8 data. As for cumulus clouds, the asymmetry factor ζ and the albedo ω are set to 0.85 and 1.0, respectively. For the detailed form of \mathcal{R} , please refer to [KR04].

3.3. Cloud Shadow Computation

The information of cloud shadow is used to evaluate the parameters for the lapse rate model described in Section 4. In our method, a cloud shadow is detected by combining a geometry-based technique and a spectral-test-based technique.

We first construct a cylinder-shaped bounding volume for a given cloud, computing the potential cloud shadow area. The ground in a local region is assumed to be plane. Due to the lack of precise cloud top height, the bounding volume is set to have a flat base surface and a flat top surface to avoid missing any true cloud shadows. Therefore, the base surface height should be lower than all of the actual cloud base height. In our tests, this base surface height is set to a low value, i.e., 50m, as no clouds exist below this altitude.

As the atmospheric lapse rate γ [Har94] describes temperature

changing with altitude, we use it to estimate the top surface height of the bounding volume, i.e. :

$$\gamma = g \frac{1 + \frac{L_v r_v}{R_d T}}{c_{pd} + \frac{L_v^2 r_v \epsilon_{dw}}{R_d T^2}} \quad (4)$$

where g is gravitational acceleration, $c_{pd} = 1004.64 J(kg \cdot K)^{-1}$ is the specific heat at constant pressure of dry air, r_v is the mixing ratio of water vapor, L_v is the latent heat of vaporization, $R_d = 287 J kg^{-1}$ is the gas constant for dry air, $\epsilon_{dw} = 0.6220$ is the ratio of the gas constants for dry air and water vapor, and T is the temperature. Using the lapse rate, a cloud top surface height Z_{ct} [ZW12, YLHY13] can be approximately estimated as :

$$Z_{ct} = (T_g - T_{ct}) / \hat{\gamma} \quad (5)$$

For dry air, $r_v = 0$, and $\gamma = \frac{g}{c_{pd}} = 9.8 K km^{-1}$. For wet air, $r_v > 0$, the lapse rate γ is not a constant, and a representative value for γ is $5.0 K km^{-1}$. Hence, we use a small lapse rate (e.g., $\hat{\gamma} = 4.8 K km^{-1}$) to estimate the top height of the bounding volume. If a predicted location falls onto a pixel identified as cloud free, the pixel is marked as a potential shadow.

Then the spectral test is applied to eliminate non-shadow pixels. The spectral features of each pixel within the possible shadowed area are inspected to detect the shadow pixels of each cloud by [LTK08]. The classification is shown in Fig. 2(b).

4. Cloud Scene Modeling

Cumulus clouds, as a typical type of low-altitude cloud, are generally dense and possess an uneven quasi-surface. Accordingly, their shape can be represented by a surface mesh [YLH*14]. However, because the sensors of polar-orbit satellites, e.g., Landsat-8, are directed toward the Earth's surface, it is difficult to observe the side surface of a cloud. Following the work of [YLHY13], we assume that the shape of a cloud can be described by a cloud top surface and a cloud base surface (Fig. 4 (a)), which are represented by the cloud top height Z_{ct} and the cloud base height Z_{cb} , respectively. Then the matching points between the boundary vertices of the top surface and the base surface are directly connected to form the side surface. Hence, the proposed modeling process is mainly divided into two steps (Fig. 3). First, using the lapse rate model and the spatially continuous constraint, we simultaneously estimate the cloud top height and the cloud base height. The reconstructed shapes are then refined and represented by a particle system for rendering.

4.1. Lapse Rate Model

Based on the hypothesis of cloud shape, we can use the atmospheric lapse rate and temperatures to describe it. Because the lapse rate has a wide range of values, it is not reasonable to assign a constant lapse rate for every cloud in a large scene. Hence we assume each cloud has a distinct lapse rate, and the cloud top height Z_{ct} can be estimated by Eqs.(5). Similarly, the cloud base height Z_{cb} can be derived from the relative difference between the ground temperature T_g and the cloud base temperature T_{cb} .

The cloud shape S is finally related to four parameters: T_{ct} , T_g , T_{cb} , and $\hat{\gamma}$ (Fig. 4 (b)). Because both the temperature T_{ct} and T_g can

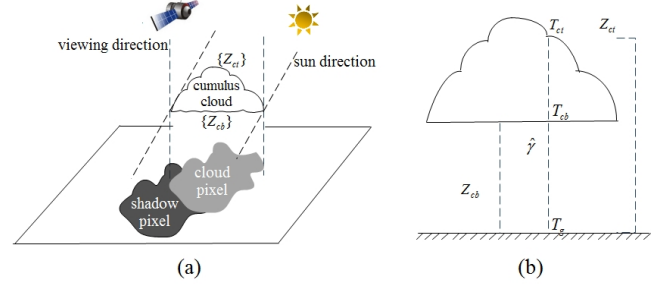


Figure 4: (a) The surface of a cumulus cloud. (b) The lapse rate model. The shape (Z_{cb}, Z_{ct}) of the cloud is correlated with temperatures (T_{ct}, T_g, T_{cb}) and the lapse rate $\hat{\gamma}$.

be derived from satellite images, the shape S is thus determined by the last two parameters, i.e., T_{cb} and $\hat{\gamma}$, as follows:

$$S \triangleq S(T_{cb}, \hat{\gamma}) \quad (6)$$

There are a lot of ground-based observations supporting the empirical rules, which define cumulus clouds as having a horizontal base surface and a cauliflower-shaped top surface (www.srh.noaa.gov/jetstream/clouds/cloudwise/types.html). These observations allow us to assume that the base surface of a cumulus cloud is flat and can be represented using a single height value. Because the ground temperature T_g and $\hat{\gamma}$ are constant within the local region covered by a cloud, the cloud base temperature can also be represented using a single value [BSW*92, ZW12]. This assumption significantly reduces the complexity for recovering a complete cloud base height field while retaining the photorealism of reconstructed cumulus clouds to a certain extent.

Given the shape of a cloud, the viewing direction of the satellite sensor, the solar zenith angle, and the solar azimuth angle, we can predict the set of cloud shadow pixels casting on the ground based on the geometric relation between a cloud and its shadow. For each cloud, denote the calculated shape by S , its shadow by CS , the original shape by S^* , and its original shadow recorded in the satellite image by CS^* . If the calculated shape approaches the original shape, their shadows will be similar in area, and the overlapping area between the original shadow and the calculated shadow will approach the area of the union of these shadows:

$$\int_{CS \cap CS^*} dx dy \rightarrow \int_{CS \cup CS^*} dx dy \text{ when } S \rightarrow S^* \quad (7)$$

In this sense, the similarity function between their shadows can be defined as the ratio of two areas:

$$SF(T_{cb}, \hat{\gamma}) = \frac{\int_{CS \cap CS^*} dx dy}{\int_{CS \cup CS^*} dx dy} \quad (8)$$

As mentioned before, the shape parameters T_{cb} and $\hat{\gamma}$ jointly determine the shape S ; the similarity function SF is therefore an implicit function of these two unknown scalars.

Denote the horizontal resolution of the satellite data by DX (in

meters per pixel). Suppose the shadow of a cloud only consists of two neighboring shadow pixels, separating by a distance DX (in meters per pixel). So, the geometrical thickness of the cloud is equal to $DX / \tan \theta_s$ according to the cloud-shadow geometry, where θ_s is the solar zenith angle [BSW*92]. In this scene, the vertical resolution can be considered as $DX / \tan \theta_s$, and the target shape of the cloud (Z_{ct}, Z_{cb}) is formulated in a discrete space. Equivalently, it is reasonable to treat the domain of the definition of T_{cb} or $\hat{\gamma}$ as a discrete space.

Because the similarity function SF is determined by two parameters, there may exist more than one solution maximizing the function. The amount of moisture in the air, determining the lapse rate, is continuous, and the lapse rate is thus spatially continuous. Therefore, the neighboring clouds should have similar lapse rates. When the lapse rates of the neighboring clouds are available, we can estimate the current cloud's lapse rate. Then, we can retrieve the optimal value of T_{cb} . In Section 4.3, we show a propagation procedure to solve our model for all clouds within a scene.

4.2. Initial Cloud Shape Estimation

The aim of this section is to determine two shape parameters for each cloud, i.e., T_{cb} and $\hat{\gamma}$, which maximize the similarity function:

$$\max_{\substack{T_l \leq T_{cb} \leq T_u \\ \hat{\gamma}_l \leq \hat{\gamma} \leq \hat{\gamma}_u}} SF(T_{cb}, \hat{\gamma}) \quad (9)$$

where T_l and T_u are the lower and upper limits for T_{cb} , respectively, and $\hat{\gamma}_l$ and $\hat{\gamma}_u$ are the lower and upper limits for $\hat{\gamma}$, respectively. Under standard atmosphere conditions, the lapse rate for wet air near the cloud top surface is 5.0 K km^{-1} , and for dry air near the ground, it is 9.8 K km^{-1} . Therefore, we set $\hat{\gamma}_l = 4.8$, and $\hat{\gamma}_u = 10$. For the cloud base temperature, the lower limit is set as the minimal temperature in the cloud region, i.e., $T_l = \min_{p \in \bar{C}} T_{ct}(p)$, while the upper limit is set as the ground temperature, i.e., $T_u = T_g$.

If the sampling intervals for the two parameters are both known, the sample set $\{T_{cb}^i, \hat{\gamma}^j\}$ can be formed by discretizing the rectangular definition domain $[T_l, T_u] \times [\hat{\gamma}_l, \hat{\gamma}_u]$. As previously mentioned, the shape of the cloud has a vertical resolution of $dz = DX / \tan \theta_s$. Here, we can use the vertical resolution dz to determine the sampling intervals for T_{cb} and $\hat{\gamma}$. The lapse rate $\hat{\gamma} \in [\hat{\gamma}_l, \hat{\gamma}_u]$ is defined as the amount of temperature decreasing per 1km, and the amount of temperature decreased $d\hat{\gamma}$ for height dz should satisfy $\frac{d\hat{\gamma}}{dz} = \frac{\hat{\gamma}}{1 \text{ km}}$. Accordingly, it is enough to set the sampling interval $d\hat{\gamma}$ for the lapse rate as $d\hat{\gamma} = \hat{\gamma}_l dz = 4.8 DX / \tan \theta_s$. Given the lapse rate $\hat{\gamma} \in [\hat{\gamma}_l, \hat{\gamma}_u]$, $\frac{dT}{dz}$ is thus less than $\hat{\gamma}_u$ for any height dz . Therefore, the sampling interval dT for the cloud base temperature should satisfy the condition: $dT \leq \hat{\gamma}_u dz = 10 DX / \tan \theta_s$.

Once the set of samples $\{T_{cb}^i, \hat{\gamma}^j\}$ has been generated, the similarity function SF is computed for each sample, and a sample is treated as a feasible solution if it maximizes the similarity function.

4.3. Large-scale cloud scene modeling

In order to model a large cloud scene, the optimal solutions of each cloud should satisfy the physical constraints of the scene where the lapse rates of clouds should be spatially continuous. According to

the number of solutions, we classify clouds into two sets: one is the set with a single optimal solution $\mathcal{C} = \{C_1, C_2, \dots, C_m\}$, and the other is the set with more than one solution $\bar{\mathcal{C}} = \{\bar{C}_1, \bar{C}_2, \dots, \bar{C}_n\}$. In our experiments, the amount of clouds in the set \mathcal{C} reaches about 30% of all clouds in a cloud scene. For the set $\bar{\mathcal{C}}$, we perform a propagation procedure to choose the optimal solutions.

The set of neighbors, $N(\bar{C}_j)$, is determined as:

$$N(\bar{C}_j) = \{C_i \in \mathcal{C} | d_{ij} \leq r\} \quad (10)$$

where r is the effective radius of the neighborhood given by users and d_{ij} is the Euclidean distance between C_i and \bar{C}_j . We first judge the optimal solution for the one with the most neighbors. We estimate an expected value for the cloud using the lapse rate of neighbors. Due to the local uniformity of the lapse rate, the nearer the distance is, the more information the cloud contributes to estimating the expected value, $\hat{\gamma}_{exp}$, which is calculated with a weighted average of the value. Let λ_j be the weight for the cloud C_j , the expected value is given by:

$$\hat{\gamma}_{exp} = \sum_{j=1}^{|N(\bar{C}_k)|} \lambda_j \hat{\gamma}^j = \sum_{j=1}^{|N(\bar{C}_k)|} \frac{\frac{1}{d_{kj}}}{\sum_{j'=1}^{|N(\bar{C}_k)|} \frac{1}{d_{kj'}}} \hat{\gamma}^j \quad (11)$$

We then pick the feasible solution, $\hat{\gamma}^j$, that minimizes $|\hat{\gamma}^j - \hat{\gamma}_{exp}|$, as the optimal solution, $\hat{\gamma}_{opt}^k$. Finally, C_k is removed from $\bar{\mathcal{C}}$ and is added to \mathcal{C} . The above process is repeated until the set $\bar{\mathcal{C}}$ becomes empty. The propagation procedure is shown in Algorithm 1.

Algorithm 1 Propagation Procedure.

Input: $\mathcal{C}, \bar{\mathcal{C}}, r$
Output: $\hat{\gamma}_{opt}^k$ for each $\bar{C}_k \in \bar{\mathcal{C}}$

- 1: **repeat**
- 2: **for all** $\bar{C}_j \in \bar{\mathcal{C}}$ **do**
- 3: $N(\bar{C}_j) = \{C_i \in \mathcal{C} | d_{ij} \leq r\};$
- 4: **end for**
- 5: find $\bar{C}_k \in \bar{\mathcal{C}}$ by maximizing the $|N(\bar{C}_k)|$;
- 6: **for all** $C_{i'} \in N(\bar{C}_k)$ **do**
- 7: $d_{ki'} = \| \bar{C}_k - C_{i'} \|_2;$
- 8: **end for**
- 9: calculate $\hat{\gamma}_{exp}$ according to Eqs. 11;
- 10: find $\hat{\gamma}^j$ by minimizing the $|\hat{\gamma}^j - \hat{\gamma}_{exp}|$;
- 11: $\hat{\gamma}_{opt}^k = \hat{\gamma}^j;$
- 12: $\mathcal{C} = \mathcal{C} \cup \{\bar{C}_k\};$
- 13: **until** $\bar{\mathcal{C}} = \emptyset$

At this point, we have constructed the initial shape (Z_{cb} and Z_{ct}) for each cloud in the scene. In Fig. 2 (c), the calculated shadow is formed by projecting the initial (calculated) shapes of the clouds onto the ground.

4.4. Cloud Shape Refinement

After recovering the top height Z_{ct} and base height Z_{cb} , a tower-shaped cloud surface is constructed using three parts, i.e., the top surface, the base surface, and the side surface (Fig. 5 (a)). To obtain highly realistic results, the cloud surface must be enriched with fine-scale volumetric structures. A fractal method [NDN96] is used

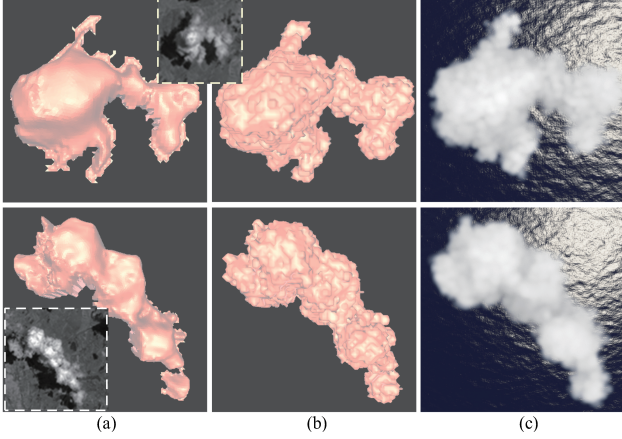


Figure 5: Top views of cloud shape refinement. (a) The initial surface. (b) The refined surface with more fractal details than (a). (c) The cloud generated by filling the region inside the refined surface with particles. The inset is the cloud region in the NIR image.

to generate fine-scale details for a cloud. A regular 3D grid is created by subdividing the bounding box of the cloud surfaces. Each grid point (x_i, y_j, z_k) has two scalar properties: the distance to the surface and the extinction value. The distance scalar is the minimum of the distances to the three surfaces. The value is normalized and denoted by \tilde{d} . The extinction σ for a cloudy pixel can be estimated from the optical thickness and the geometrical thickness $Z_{ct} - Z_{cb}$ as follows:

$$\sigma = \min(\tau / (Z_{ct} - Z_{cb} + DX), 90) \quad (12)$$

The spatial resolution DX is used to avoid division by zero. Due to our flat cloud base assumption, the geometrical thickness for pixels in the boundary region is relative small, leading to an overestimation of the cloud extinction σ . We limit the value of σ to be less than a typical value of 90km^{-1} for cumulus clouds [BNM*08]. So, the extinction of a point is set to that of the corresponding pixel (x_i, y_j) if $Z_{cb} < z_k < Z_{ct}$. Otherwise, the extinction is set to 0. Starting from the distance field, we apply [NDN96] to generate surface fringes by iteratively placing metaballs at the surface of the cloud. Because the base surface is relatively flat, a larger radius is used for the metaballs compared to those for the top surface. Finally, a mass of metaballs with various radii are arranged on the cloud surface. For the refined cloud shape, the extinction volume is updated accordingly using nearest-neighbor interpolation.

Similar to [YLH*14], each cloud is filled with particles by an adaptive sampling process. The process will generate a density field for each cloud, which shows the distribution of the cloud particles with various extinction. The refined cloud shapes and the rendering results are shown in Fig. 5.

5. Results

In this section, we mainly verify the accuracy of feature extraction, physical soundness and validity of our modeling method, as well as showing some applications.

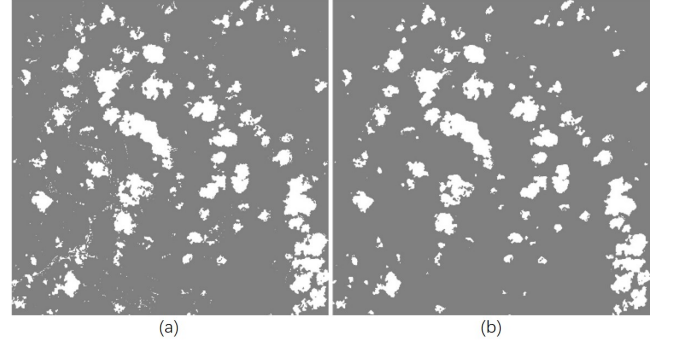


Figure 6: Qualitative comparison of two methods for cloud masks. (a) Oreopoulos et al.'s result. (b) Our result.

Our work is implemented on a PC with an i5-2300 Intel(R) Core(TM) 2.8GHz CPU, an NVIDIA GTX 460 card, and 4GB of RAM. Five-band satellite images from Landsat-8, described in Section 3, are used in the work as inputs. Note that the satellite images provided by other satellites, e.g., Landsat-7 or Terra, can also be used as long as the satellite images have the five bands. The Landsat-8 image data, along with a text file with metadata (date and time, longitude and latitude, solar azimuth and zenith), can be downloaded freely at <http://landsat.usgs.gov/>. For these images, the first four bands have a resolution of 30 m while the last one has a resolution of 100 m and is resampled to 30 m, and the zenith angle of the sun is less than 30° , it is hence reasonable to set $d\gamma = 0.1$ and $dT = 0.3$.

The size of the original Landsat-8 satellite images is 7821×7641 . To test our methods, we choose some parts of the original images, containing more cumulus clouds, as the input. There are three subimages of the original images in our experiments. The first scene from the first subimages was captured at 02:18:35 UTC on 28th June 2013 and has a size of 650×650 . The longitude range is $121.44E \sim 121.62E$ and the latitude range is $17.66N \sim 17.84N$. The second scene was captured at 02:16:40 UTC on 12th April 2014 and has a size of 950×950 . The longitude range is $121.62E \sim 121.88E$ and the latitude range is $16.46N \sim 16.72N$. The third scene was captured at 02:16:25 UTC on 28th April 2014 and has a size of 791×791 . The longitude range is $121.31E \sim 121.53E$ and the latitude range is $17.98N \sim 18.20N$. The average time to model each cloud is approximately 5s, of which 3s is required to search for the shape parameters in the cloud shape estimation. The numbers of clouds in the three scenes are 77, 169 and 125, respectively.

5.1. Comparison on Feature Extraction

We compare against the state of the art [OWV11] in cloud detection. Fig.6 shows the qualitative comparison of cloud detection with [OWV11], which performs on par with the ACCA algorithm. The scene shown in Fig.2(a) is used as the input image. As shown in Fig.6(a), although [OWV11] can mark the cloud pixels, a large amount of noise are also picked up. In contrast, our method can better identify the cloud pixels with fewer errors.

We also performed comparisons against the manual annotation

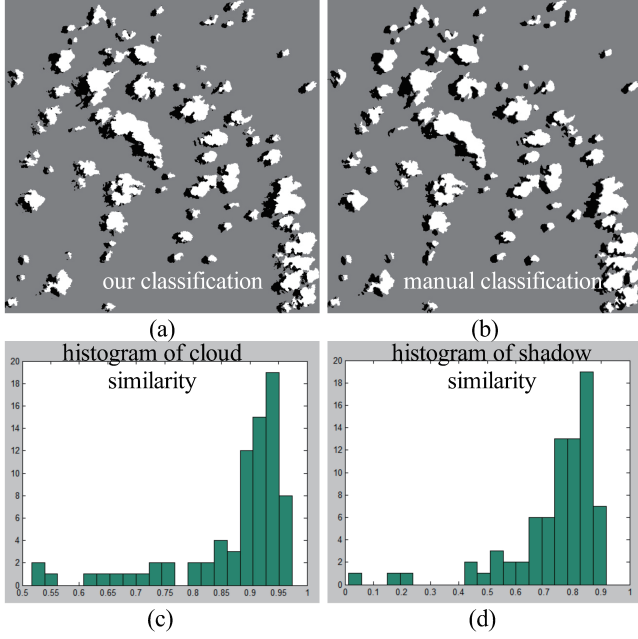


Figure 7: (a) Our cloud-shadow mask. (b) The manual cloud-shadow mask. (c) The similarity histogram for all pairs of clouds. (d) The similarity histogram for all pairs of cloud shadows.

method. Masking cloud shadows from normally illuminated surface conditions is difficult [ZW12], therefore the manual method becomes a better way for screening cloud shadows. We ask three experienced meteorologists to label mask. They mask cloud and cloud shadow separately in Adobe Photoshop, and the average of the three results is used as the final manual result to reduce man-made errors. By comparing our cloud-shadow mask with the manual mask, it shows that the accuracy of our automatic classification algorithm approaches the accuracy level of the manual method especially for cloud detection as shown in Fig.7. Without ambiguity, we use C_i and CS_i to represent the pixel set of each cloud and that of the cloud shadow in our mask, respectively, and use C_i^m and CS_i^m to represent their corresponding pixel sets in the manual mask. To qualitatively evaluate our mask, the similarity of the two pixel sets, e.g., C_i and C_i^m , is defined as $S(C_i, C_i^m) = \frac{|C_i \cap C_i^m|}{|C_i \cup C_i^m|}$. From (c) and (d), 83% of clouds have similarity greater than 0.8, 75% of cloud shadows have similarity greater than 0.7. For the whole scene, the cloud similarity is $\frac{\sum_i |C_i \cap C_i^m|}{\sum_i |C_i \cup C_i^m|} = 90\%$, but the cloud shadow similarity is relatively low, i.e., $\frac{\sum_i |CS_i \cap CS_i^m|}{\sum_i |CS_i \cup CS_i^m|} = 72\%$, due to the relatively small size of cloud shadows compared to the clouds in the scene. In general, the accuracy of our mask is close to the latest method [ZW12] in which the cloud similarity is 96% and the cloud shadow similarity is about 70%.

To our knowledge, there is no automatic method to accurately calculate cloud height. In order to investigate the validity of our method, we compare our method with the manual annotation method. In both methods, the basic idea is that the cloud and its shadow have similar shapes. Three analysts first select highly dis-

tinguishable points on the cloud edge and the corresponding points on the shadow edge in the solar azimuth direction. Then, the cloud base height Z_{cb}^m is estimated from the separation distance d between the matching pair of points based on the cloud-shadow geometry, i.e., $Z_{cb}^m = d / \tan \theta_s$. For the three subimages, the experiment results show that the differences between our method and the manual method in terms of the determined average cloud base heights are approximately 85m, and the differences of standard deviations between both methods are in the order of 38m. Considering the resolution of the satellite images, ranging from 30 m to 100 m, it shows that our method yields similar results as the manual method.

We further test the shape errors taken by the fractal method which is used to generate details for clouds. As mentioned before, we use C_i^f to represent the pixel set of each cloud, then the cloud similarity is $\frac{|C_i \cap C_i^f|}{|C_i \cup C_i^f|} = 98.49\%$. The result reveals that the fractal method produces less error.

5.2. Comparison on Cloud Scene Modeling

[YG15] is the most closely related to our method. In contrast, we improve by generating more physically reliable and accurate cumulus clouds. First, [YG15] applied a constant lapse rate assigned by user to calculate cloud base heights for all clouds in a scene. Instead, our method automatically calculates a physical sound lapse rate, which satisfies the physical constraints of a large-scale scene, for each cloud separately by using the lapse rate model. So, if a cloud does not meet the constant lapse rate, our method can improve the estimate of the cloud base height accuracy, Ar , by:

$$Ar = \frac{|Z_{cb}^{con} - Z_{cb}^{uniq}|}{Z_{cb}^{uniq}} = \frac{|\lambda_{con} - \lambda_{uniq}|}{\lambda_{con}} \quad (13)$$

where λ_{con} is the constant lapse rate, λ_{uniq} denotes the unique lapse rate of each cloud calculated by our method. Z_{cb}^{con} and Z_{cb}^{uniq} are the cloud base heights calculated by using the λ_{con} and the λ_{uniq} , respectively. If λ_{con} and λ_{uniq} are set to 6.5 and 7, respectively, the accuracy will improve by 7.14 percent according to the Eqs.(13).

Second, the influence of the ground radiance on the cloud radiance is not considered in [YG15], when estimating the temperature of the cloud top surface. In contrast, our method uses a linear combination of the ground radiance and the cloud radiance to obtain more accurate cloud top temperature. Third, the cloud base height was computed by averaging the height for all the pixels on the edge of the cloud top surface in [YG15]. However, cloud usually has a small thickness along the boundary region, the measured temperature is usually higher than the actual temperature due to the contribution of the infrared radiation from the ground. So it will underestimate the cloud base height, which make clouds be close to ground. To improve the physical reliability and the accuracy of the cloud base height, we instead use the lapse rate model to calculate the height of cloud base. Finally, Fig.8 shows that our method can generate clouds with more reliable heights and photorealistic shapes, which is more useful for flight simulation and weather phenomena visualization.

Our method resembles in spirit [YLHY13, LY16] in that the cloud properties, e.g., Z_{ct} and Z_{cb} , are derived from multi-spectral

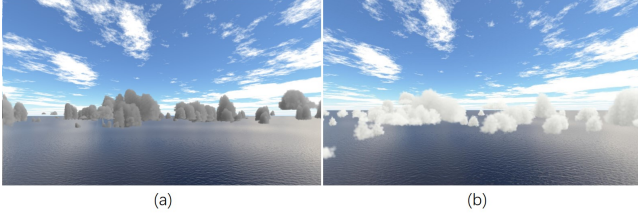


Figure 8: Comparisons of our method with the method of [YG15]. (a) Yuan et al.'s result. (b) Our result.

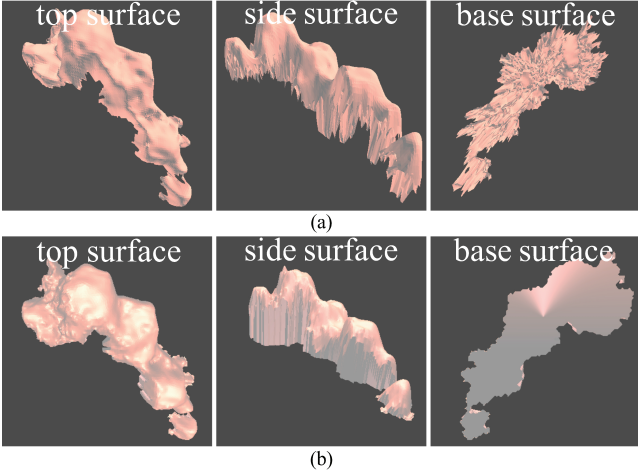


Figure 9: Comparisons of our method with the method of [YLHY13]. (a) The surface generated by [YLHY13]. (b) The initial surface generated by our method.

images. However, [YLHY13] relies on user settings (particle number density) to estimate the base height and extinction, leading to a quite random cloud base surface (Fig. 9 (a)), which is a needle-like structure spreading across the entire base surface. Although, the method [LY16] gives a more comprehensive analysis on the method [YLHY13], it also uses a given constant lapse rate to estimate the cloud base height. Such an unnatural result is inconsistent with the observation that cumulus clouds usually have a horizontal base. Instead, our method can produce quite flat base surface (Fig. 9 (b)), because the physically sound parameters.

Our method resembles in goal [DNYO98] generating a density volume by inverting a simplified model. But [DNYO98] has difficulty in recovering a reasonable cloud shape, as reported in [YLHY13], since, it does not consider the physical reasonableness of clouds height and the global physical constraints of cloud scenes.

5.3. Validation Using Numerical Simulation Data

Fig.10 provides the validity evaluation. Because it is not easy to gather real 3D cloud data, we use the outcome of the WRF model [NCA] to construct the ground-truth cloud. The data set consists of 80 time steps in the time interval of 10 minutes, recording a part of

the lifecycle of a cumulus cloud. The dimensions of the data set are $81 \times 81 \times 71$ voxels organized on a rectilinear lattice.

The data set includes multiple variables with a horizontal resolution of 100 m and a vertical resolution of 50 m. We use two variables, i.e., the cloud particle/air mass ratio mr and the temperature T . A voxel with $mr > 0$ is treated as a cloudy voxel, otherwise, it is treated as a cloud-free voxel. From this classification, the cloud surface is extracted using the Marching Cubes algorithm. Then, the reference cloud top height z_{ct}^r and cloud base height z_{cb}^r are generated from the cloud surface. From the cloud top height, the cloud top temperature T_{ct} can be generated by interpolating the temperature variable T . The ground temperature T_g is treated as the temperature at the bottom of the simulation lattice. In addition, the cloud shadow is formed by projecting the cloud surface onto the ground.

Once the cloud top temperature, ground temperature, and cloud shadow are available, our method is used to reconstruct the cloud base height Z_{cb} and the cloud top height Z_{ct} . The average value of the lapse rates $\frac{T_g - T_{ct}}{Z_{ct}}$ for all cloudy pixels is used to determine the optimal shape parameters. In Fig. 10, the results of three phases for the formation of a cumulus cloud, including (a) the formative phase, (b) the developing phase, and (c) the mature phase. From the three results, the standard error of the cloud base height and that of the cloud top height are 350 m and 278 m respectively. In this scene, for cumulus cloud, our method performs better than the standard method [WTM11] based on its standard error of 800 m for the cloud base height and on the resulting error of 500 m for the cloud top height. Furthermore, the calculated shape, as well as the calculated shadow, is similar to the ground-truth shape.

5.4. Applications

In this section, we showcase two multimedia applications. The particle-based representation allows the generated clouds to be easily integrated with other graphics models, such as ocean, and sky. Fig.1 and Fig.11 reveals several applications integrating clouds with some different scenes. To present our results better, we give a video to demonstrate the integrating results with ocean scene simulated using [BNH10].

The data of clouds could also be used to improve visualization effect of GIS system. In the experiment, according to latitude and longitude values of satellite images, we add the clouds modeled to the corresponding area of an earth model loaded by osgEarth. Fig.12(a) depicts the original satellite image used to model clouds. Fig.12(b) is the original earth model. Fig.12(c) shows the result of adding clouds to the original model. As shown in Fig.12, the technique promotes the appeal of the GIS system.

6. Conclusion

We present a new physically based framework for modeling cumulus cloud scene from high-resolution satellite images. The key to our framework is estimating a reliable cloud shape by jointly using the shadow and temperature information recorded in satellite images. For this, the data processing and the lapse rate model are proposed for getting physically sound modeling parameters. The shape parameters are determined by maximizing the similarity between the reconstructed shadow and the original shadow. Based on

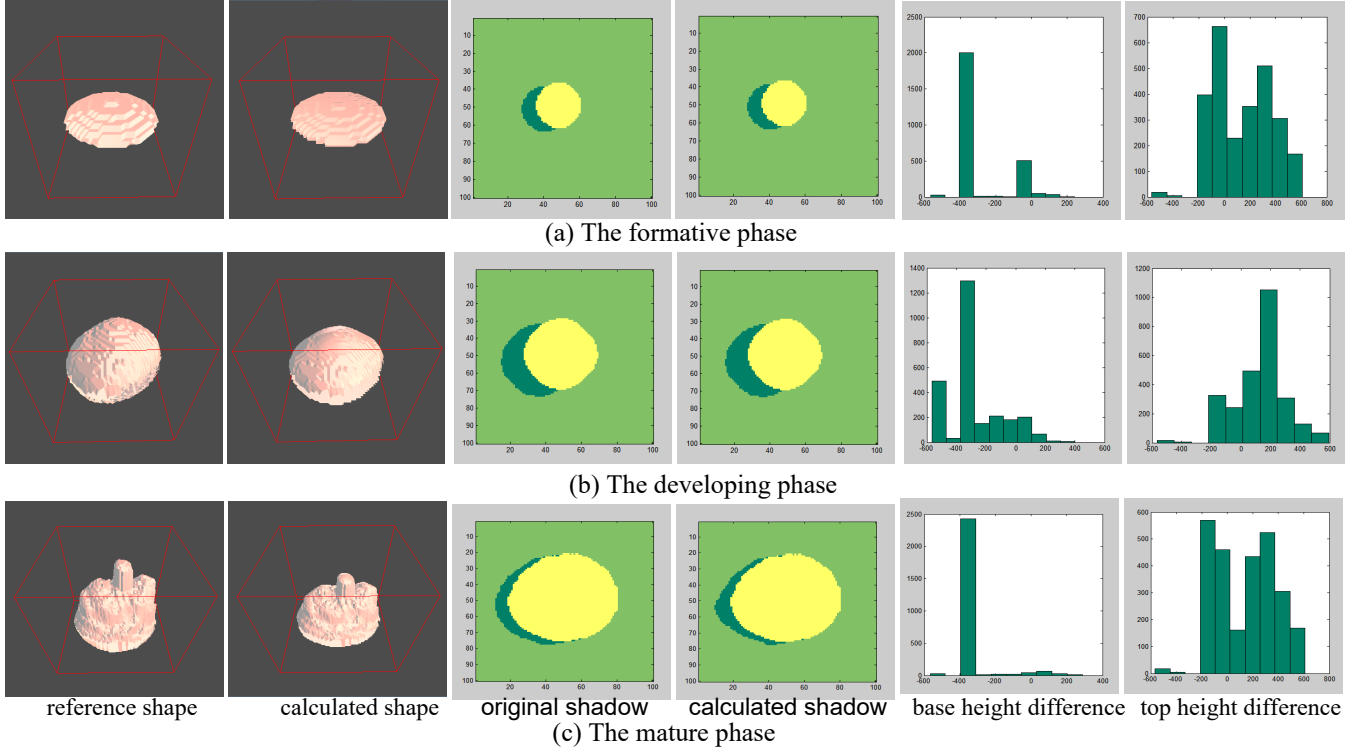


Figure 10: Validation of our method using WRF data. Each row shows a phase for the formation of the cumulus cloud, including the formative phase, the developing phase and the mature phase.



Figure 11: Four examples of integrating with different scenes for the reconstructed cumulus clouds.

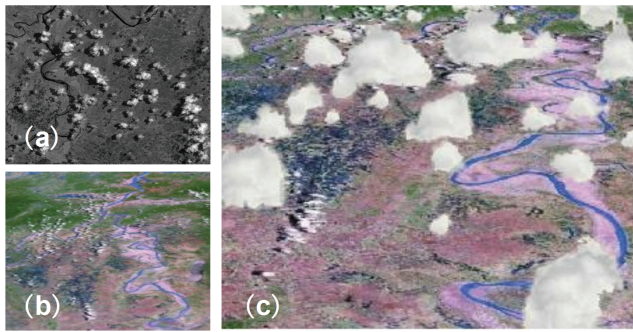


Figure 12: Example of enhance display effect of the virtual earth. (a) The original satellite image. (b) The original earth model. (c) The earth model with clouds generated by our method.

these, we can automatically recover the geometry of clouds from multi-spectral images. Experiment results have demonstrated the effectiveness and efficiency of our framework in modeling a large-scale cumulus cloud scene from satellite images. In the future, we are interested in extending this framework to simulate the evolution of cumulus clouds. Incorporating ground-based observation data, such as lidar data, to facilitate the evaluation and the recovery of the cloud base height is also an interesting research direction.

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